Biobjective Aircraft Route Guidance through Convective Weather

Kenneth Kuhn
Department of Civil and Natural Resource Engineering
The University of Canterbury, New Zealand
Email: kenneth.kuhn@canterbury.ac.nz

Andrea Raith
Department of Engineering Science
The University of Auckland, New Zealand

1 Introduction

Convective weather is a leading source of air travel delay. Pilots flying through areas where convective weather is present select routes aiming to minimize risk and maximize efficiency. Air traffic controllers suggest routes pilots may accept or decline, while also estimating airspace capacities, scheduling aircraft landings, and performing a host of other activities all related to considerations of risk and uncertainty. The goal of this research is to provide aircraft route guidance during periods of convective weather. This work is differentiated from past work in that the problem is explicitly modelled as a biobjective problem and solved to optimality, giving pilots flexibility to choose from a set of non-dominated routes minimizing risk and maximizing efficiency. There are many different efficient algorithms to solve such a biobjective shortest path problem to optimality [1]. There are likewise many ways to define risk including methods based on the evolution of weather patterns over short periods of time or pilot and controller reactions to given weather patterns [2].

2 Weather and Risk

The trajectories of aircraft flying through convective weather are most strongly related to two forms of data currently collected: vertically integrated liquid and radar echo top measurements [3]. Vertically integrated liquid data shows precipitation intensity by latitude and longitude at different times, and is typically transformed to a six point scale known as VIP or NWS level. Radar echo tops show cloud heights and are typically measured in thousands of feet. In much past research, aircraft are assumed or advised not to fly through discs, squares, or other convex shapes covering all areas reporting VIP levels three and higher [4, 5]. Algorithms then select routes that are optimal in terms of distance travelled. The assumption that pilots avoid VIP level three and higher areas is common in aviation systems engineering and the various covering shapes are used to ease computational burdens.

The past research ignores empirical evidence that VIP level three holds relatively little significance for pilots; see [2, 6] and other studies. One case study found the VIP level three threshold rule of thumb "in some cases, was too conservative" and in other cases "declared as passable regions that pilots consistently avoided" [6]. Radar echo top data is actually a stronger predictor of pilot behavior than VIP level; again see [2, 6] and other studies. Actually, aircraft altitude, echo top height, and VIP data should all be considered [2]. A common, often unstated, finding of empirical studies is that it is impossible to accurately select weather conditions pilots as a group will fly through vs. those they will avoid. Different pilots will have different concerns, available options, knowledge of the weather, etc.. It is also worth noting that it is notoriously difficult to predict how weather patterns will evolve even over limited periods of time. Given all this, it is unrealistic to assume as given a four-dimensional map bifurcating airspace into areas safe and unsafe to fly through some time into the future.

3 Methodology

We model the route flown by an aircraft as a path in a flight network. The airspace is discretized into a grid, where every grid cell is represented by a node. Nodes are connected to adjacent nodes in the eight neighboring grid cells via arcs. A path in this network represents the approximation of a possible route an aircraft may follow through airspace. For a preliminary study, we assume a fixed flight level and a relatively short time period and thus obtain a 2-D flight network. It is easiest to conceptualize the 2-D problem, so we focus on that in this extended abstract. In this study, flight networks considered include hundreds of thousands of nodes.

We measure the efficiency of an aircraft route in terms of distance flown, which forms the first route choice objective. The second objective is minimizing risk along the route. A risk factor between 0 and 1000000 is assigned to each arc in the network, where the higher the risk factor, the less attractive an arc is. In this study, higher risks are associated with weather conditions that fewer pilots were observed flying through in the largest empirical study to date [2]. We wish to primarily capture the fact that different pilots have different tolerances for the maximum level of risk they are willing to accept in any part of their flight path. Secondarily, trajectories involving shorter paths through unattractive weather are favored. In order to achieve the desired results, we transform the results of the cited study and assign risk factors of varying orders of magnitude.

For example, areas reporting conditions that anywhere between 30 and 40% of pilots avoided are assigned one risk factor while areas reporting conditions that anywhere between 40 and 50% of pilots avoided are assigned a significantly higher risk factor. [7] also consider exposure to weather as an objective component in the form of "normalized weather intesity" but it remains unclear how the corresponding objective is formulated. Only simulated radar reflectivity showing precipitation intensity is used to determine weather cell severity but echo top measurements are not considered.

Let $n \in \mathcal{N}$ denote a node and $(i,j) \in \mathcal{A}$ with $i,j \in \mathcal{N}$ an arc in the flight network. The set $\mathcal{P}_{s,t}$ is the set of paths (or routes) in the flight network connecting origin node s to target node t. The length of an arc (i,j) is d_{ij} and its risk factor is r_{ij}. The distance traveled along a path is obtained by summing the length of the arcs, $d(p) = \sum_{(i,j)\in p} d_{ij}$, and the risk along a path is obtained correspondingly, $r(p) = \sum_{(i,j)\in p} r_{ij}$. The biobjective aircraft route choice problem is then

$$\begin{aligned} \min \quad & \begin{pmatrix} d(p) \\ r(p) \end{pmatrix} \\ \text{s.t.} \quad & p \in \mathcal{P}_{s,t}. \end{aligned} \tag{1}$$

Our aim is to identify *efficient* routes of (1) with the property that it is not possible to obtain a route with better objective value in one component without worsening the other component. This set of paths represents the best trade off solutions between the most direct and the safest paths and thus constitute a route choice set for pilots – it is likely that pilots will choose one of these routes, but which route is chosen may depend on pilot preference and experience.

While a similar problem has been approximately solved using heuristics [7], there does not seem to be a need to do so as several exact algorithms as discussed in [1] are capable of quickly identifying all efficient solutions. For one example instance involving weather reported around Atlanta, Georgia on 5 May, 2007 at 11:00 GMT, we create a flight network with 122304 nodes and 974236 arcs which is considerably larger (more than two orders of magnitude) than the one considered in [7] and also based on real weather data. To solve (1) for this flight network, we use a biobjective label setting algorithm which extends the single-objective label setting algorithm, also known as Dijkstra's algorithm, to the biobjective case. We are able to identify all efficient solutions with this biobjective label setting algorithm on a standard desktop computer within 1 second without taking advantage of any speedup techniques or network preprocessing.

Some of the obtained efficient paths are shown in Figure 1, where origin and destination are circled. The route shown in white is the most direct one, the left-most route shown in black is the safest one and the other routes shown in green have intermediate safety and distance values.

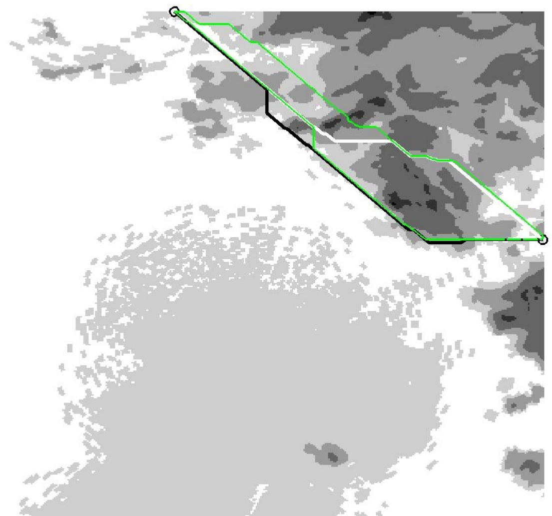

Figure 1: Risky weather and efficient flight paths.

References

[1] A. Raith and M. Ehrgott, "A comparison of solution strategies for biobjective shortest path problems", *Computers and Operations Research* 36, 1299-1331 (2009).

[2] K. Kuhn, "Analysis of Thunderstorm Effects on Aggregate Aircraft Trajectories", *Journal of Aerospace Computing, Information, and Communication* 5, 108-119 (2008).

[3] D. Rhoda and M. Pawlak, "The Thunderstorm Penetration/Deviation Decision in the Terminal Area", AMS Conference on Aviation, Range, and Aerospace Meteorology, Dallas, 1990.

[4] J. Prete and J. Mitchell, "Safe Routing of Multiple Aircraft Flows in the Presence of Time-Varying Weather Data", AIAA Conference on Guidance, Navigation and Control, Providence, 2004.

[5] J. Pannequin, A. Bayen, I. Mitchell, H. Chung, and S. Sastry, "Multiple Aircraft Deconflicted Path Planning with Weather Avoidance Constraints", AIAA Guidance, Navigation and Control Conference, Hilton Head, 2007.

[6] R. DeLaura and S. Allan, "Route Selection Decision Support in Convective Weather: A Case Study of the Effects of Weather and Operational Assumptions on Departure Throughput", Eurocontrol FAA ATM R&D Seminar, Budapest, 2003.

[7] S. Alam, M.H. Nguyen, H.A. Abbas, and M. Barlow, "Ants Guide Future Pilots", in *Progress in Artificial Life*, 36-48, Springer-Verlag, Berlin Heidelberg, 2007.